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Structural Transformation of African Agriculture and Rural Spaces

Locus of Control and Technology Adoption in Africa: Evidence from Ethiopia

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Abstract

We investigate the implication of farmers' locus of control on their technology adoption decisions. Our empirical analysis is based on two longitudinal surveys and hypothetical choice exercises conducted on Ethiopian farmers. We find that locus of control significantly predicts farmers' technology adoption decisions, including use of chemical fertilizers, improved seeds, and irrigation. We show that individuals with an internal locus of control have higher propensity of adopting agricultural technologies, while those with an external locus of control seem less likely to adopt one or more of these agricultural technologies. We observe these empirical regularities in both datasets, and for both revealed measures of farmers' technology adoption decisions as well as farmers' hypothetical demand for agricultural technology. The results hold even in a more conservative fixed effects estimation approach, assuming locus of control as time-variant and dynamic behavioral trait. These findings provide psychological (behavioral) explanations for the low rates of adoption of profitable agricultural technologies in Sub-Saharan Africa. Our results highlight that improving farmers' psychological capital and non-cognitive skills may facilitate agricultural transformation. More generally, the results suggest that anti-poverty policies that only focus on relaxing short-term external constraints, including physical access to markets and technologies, may not sufficiently alleviate agricultural underinvestment.

Keywords: Locus of control, internal constraints, behavioral biases, technology adoption, agricultural investment, chemical fertilizers.

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I. Introduction

Adoption and diffusion of modern agricultural technologies can instrumentally facilitate agricultural transformation in developing countries (Evenson & Gollin, 2003; Gollin, 2010). Facilitating agricultural technology adoption is particularly crucial for many Sub-Saharan African countries where the aggregate technology adoption trends remain low (Morris, Kelly, Kopicki & Byerlee, 2007; Rashid, Tefera, Minot & Ayele, 2013; Sheahan & Barrett, 2014). Despite the substantial efforts and investments on promoting modern agricultural technologies, reconciling the empirical puzzle associated with the low adoption rates of profitable agricultural technologies in many African countries remains a challenge.

A large literature mainly points to external constraints of farmers as limiting factors to technology adoption in Africa. These external constraints include credit constraints, transactions costs and related market imperfections.[1] Most previous theoretical and empirical studies on technology adoption are founded on the notion that farmers are ''poor but rational'' (Schultz, 1964). This argument implies that farmers are rational profit maximizers and hence will choose the optimal level and mix of alternative agricultural technologies.[2] Duflo, Kremer & Robinson (2011) argue that the existing low level of adoption of agricultural technologies in Africa is not consistent with this view. The contradiction between empirical regularities and this neo-classical view opens a room for insight from behavioral economics that can help understand household decision making processes and technology adoption decisions.

Recently, evolving behavioral and psychological studies argue that poor households in developing countries not only suffer from external constraints, but also internal constraints and behavioral biases that may hinder profitable agricultural investments (Bertrand et al., 2004; Banerjee & Mullainathan, 2010; Duflo et al., 2011; Mullainathan & Shafir, 2013; Haushofer & Fehr, 2014; Bernheim et al., 2015). Some of these internal constraints include self-control (temptation) problems, high discounting behavior and poor intertemporal planning behavior. More generally, behavioral economists provide two relevant explanations why farmers' agricultural investment

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[1] For example, Moser & Barrett (2006), Giné & Klonner (2007), Duflo et al. (2011), and Minten et al. (2013) indicate that credit constraints and transaction costs are central factors that may limit the adoption of agricultural technologies in Sub-Saharan Africa. Along this line of reasoning, some studies show that relaxing credit constraints can improve farmers' technology adoption in Africa (e.g., Zerfu and Larsen, 2010; Lambrecht et al., 2014; Abate et al., 2016). The implications of credit constraints also extend to other types of technologies, including improved cooking stoves (Beltramo et al., 2015; Bensch et al., 2015).

[2] This argument has been a source of long debate on whether chemical fertilizer adoption should be subsidized or not.

decisions may deviate from the standard economic theory discussed above (see Mullainathan and Thaler, 2000). First, people (farmers) might be bounded rational, in the sense that they may have limited cognitive and non-cognitive ability to solve complicated intertemporal choice problems. This problem is expected to be substantial in developing countries and rural farmers with limited consumer education. Second, people (particularly the poor) may have bounded willpower due to self-control and temptation problems, which may restrict people from making optimal intertemporal choices. For instance, although farmers may realize that fertilizer adoption is the best choice, they may not actually adopt it due to self-control problems. Duflo et al. (2011) argue that farmers with time-inconsistent preferences, those with self-control problems, are less likely to invest in chemical fertilizers.

In this paper, we study the implication of a psychological concept intrinsically related with the above two types of internal constraints on technology adoption decisions of farmers in Africa. We particularly investigate the implication of farmers' locus of control on technology adoption decisions in Ethiopia, where agricultural intensification and aggregate technology adoption remain low. Locus of control stands for "a generalized attitude, belief, or expectancy regarding the nature of the causal relationship between one's own behavior and its consequences" (Rotter, 1966, p. 2).[3] Adoption of a new technology involves some intertemporal opportunity costs and uncertainty. Hence, locus of control, individuals' subjective belief about future outcomes and the extent to which these events can be affected by own actions, can affect technology adoption decisions. It is reasonable to expect that individuals with an internal locus of control, those who believe that life events can be sufficiently influenced, are more likely to invest in agricultural technologies than those with an external locus of control, those who believe that life events are more of out of their control. Previous studies show that individuals with an internal locus of control are associated with higher investment decisions, including human capital investments (Coleman & DeLeire, 2003; Heckman et al., 2006).[4] Coleman and DeLeire (2003) present a theoretical human capital investment model and show that locus of control can affect individuals' human capital investment decisions by shaping their perceived (subjective) probability of success of a specific investment. Following this conceptual framework, we aim to provide first-hand empirical evidence on the implication of locus of control

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[3] Previous psychological studies employ locus of control as one component of self-control (Rosenbaum, 1980).

[4] Most previous studies on locus of control focus on the implication of these non-cognitive skills on individuals' labor market outcomes (Coleman & DeLeire, 2003; Heckman et al., 2006; Cobb-Clark & Schurer, 2013; Caliendo et al., 2015).

on agricultural technology adoption decisions, and hence agricultural investments. Overall, this study aims to uncover some behavioral and psychological explanations to the existing low levels of adoption of profitable agricultural technologies in Sub-Saharan Africa. These explanations may also help to attribute some of the existing unexplained heterogeneities in technology adoption decisions among rural households in Sub-Saharan Africa (Suri, 2011; Sheahan & Barrett, 2014; Abay, Berhane, Taffesse, Abay & Koru, 2016).[5]

We employ two longitudinal datasets to pursue the above empirical analysis. The first dataset is a large longitudinal survey which covers the most important agricultural zones in Ethiopia. The second longitudinal dataset comes from a randomized controlled experiment conducted to evaluate the implication of weather-index crop insurance on technology adoption in Ethiopia. We investigate the implication of locus of control on farmers' actual technology adoptions as well as on their hypothetical demand for a new agricultural technology. This is particularly appealing given that locus of control may correlate with some other unobservable factors that may affect farmers' actual technology adoption decisions. Hence, using farmers' hypothetical demand for new agricultural technology may help us minimize some of the endogeneity and reverse causality problems, while also highlighting the implication of individuals' locus of control on future agricultural investments and aspirations. We elicit farmers' locus of control using Rotter's (1966) scale by employing the commonly used and contextualized list of ten items (questions) that measure farmers' degree of perceived control over their life events. We employ alternative econometric approaches that exploit the cross-sectional as well as longitudinal variations in farmers' locus of control.

We find that farmers' locus of control significantly predicts adoption of a considerable list of agricultural technologies, including chemical fertilizers, improved seeds and irrigation practices. We specifically document that those farmers with an internal locus of control (or more of it) are more likely to adopt these agricultural technologies, while those farmers with an external locus of control (or more of it) seem less likely to adopt one or more of these agricultural technologies. These empirical results hold in both datasets, as well as for both farmers' actual technology adoptions and farmers' hypothetical demand for a new agricultural technology. We probe the robustness of our results using alternative estimation and empirical strategies. We show that the results hold even

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[5] For instance, Abay et al. (2016a) document substantial heterogeneities in technology adoption decisions that cannot be explained by the commonly observable attributes and characteristics of households.

using a more conservative fixed effects estimation approach, assuming locus of control as a time-variant and dynamic behavioral trait (Boyce et al., 2013; Cobb-Clark & Schurer, 2013). These findings have important implications in terms of understanding rural households' technology adoption decisions and explaining the existing low levels of aggregate technology adoption in Africa. Our results imply that policy instruments that improve rural farmers' non-cognitive skills and psychological capital may boost farmers' agricultural investments. The results particularly highlight that anti-poverty policies in Africa may need to target not only external constraints of poor households, but also internal constraints which are expected to influence agricultural investments. Implicitly, improving farmers' agricultural investments may require integrating policies that address external constraints (for example, improving access to markets and technologies) and those that alleviate farmers' internal constraints. This is particularly crucial given that many of the earlier agricultural policies in Sub-Saharan Africa focused on addressing external constraints of farmers and related market imperfections.

The rest of the paper is organized as follows. Section 2 provides a brief review of the literature on locus of control and its implication on some behavioral and economic outcomes. Section 3 provides a description of the context and data. Section 4 describes the estimation strategies and econometric methods. Section 5 discusses the empirical results, and section 6 concludes

II. Locus of control and investment decisions: review

Recent theoretical and empirical studies acknowledge that personality traits, particularly locus of control significantly predict various economic and behavioral outcomes. These non-cognitive skills have recently been incorporated into economic and behavioral models. For instance, Coleman and DeLeire (2003) incorporate locus of control in human capital investment decisions, through which differences in individuals' locus of control enter the human capital investment model by affecting subjective probability of success of a specific investment. Almlund et al. (2011) incorporate individuals' personality traits in their economic model of decision making involving individuals' preferences and expectations. Heckman et al. (2006) study the interaction of cognitive and non-cognitive skills and their implications in predicting various behavioral and economic

outcomes. These theoretical and empirical studies mainly highlight the role of personality traits on human and physical capital investments.

Locus of control and related non-cognitive skills are also shown to explain substantial differences in other economic outcomes, including earnings and labor market outcomes (Goldsmith et al., 1997; Heineck & Anger, 2010; Caliendo et al., 2015). Other empirical studies show that locus of control explains health related investments (Chiteji, 2010; Cobb-Clark et al., 2014), while others show that internal locus of control may serve as psychological insurance against negative shocks (Buddelmeyer & Powdthavee, 2016). More recent studies also investigate the implication of locus of control on intertemporal decisions involving savings and wealth accumulation (Cobb-Clark et al., 2016; Abay, Berhane & Assefa, 2016).

The existing literature on non-cognitive skills further explores the nature and dynamics of individuals' locus of control and its interactions with other behavioral attributes. Earlier empirical studies assume that locus of control is reasonably stable and fixed across lifetime, an assumption that facilitates empirical identification of the effect of these non-cognitive skills on various economic and behavioral outcomes. Following this assumption, earlier studies in the literature exploited cross-sectional, as well as lagged (or lead) measures in these attributes to investigate the role of these variations on various economic outcomes. However, recent empirical studies cast some doubt on the stability of these attributes and hence the validity of using lagged variations in these attributes to identify their impact (Boyce et al., 2013; Cobb-Clark & Schurer, 2013). Cobb-Clark and Schurer (2013) conducted a careful investigation of the stability of locus of control and show that locus control may not be truly time-invariant while also suggesting that its dynamics are rather modest. Cobb-Clark and Schurer (2013) also characterize the short-run and medium run dynamics in locus of control and conclude that the use of lagged measures of locus of control may result in a substantial attenuation bias. Furthermore, other studies show that locus of control can be reasonably malleable and may interact with other personality traits, as well as cognitive skills that may amplify the effects of locus of control on various economic outcomes. For instance, Bernard et al. (2014) provide some experimental evidence showing that farmers' locus of control and aspirations can be improved using some inexpensive behavioral interventions. These pieces of evidence open a room for exploring other alternative empirical approaches to quantify the implication of individuals' locus of control, including those that exploit longitudinal variations in locus of control (Boyce et al., 2013; Cobb-Clark & Schurer, 2013; Cobb-Clark et al., 2014).

Although we are not aware of previous studies on the implication of locus of control on farmers' technology adoption decisions, some of the above studies provide indirect pieces of evidence that may lead to our premise. For instance, some previous studies show that individuals with an internal locus of control (or more of it) are associated with higher physical and human capital investments (Coleman & DeLeire, 2003; Heckman et al., 2006; Cobb-Clark et al., 2016). More specifically, one can theoretically fit the human capital investment model by Coleman and DeLeire (2003) to an agricultural investment model where the probabilities of realizations of future payoffs depend on farmers' locus of control and expectations.

Despite the empirical challenges associated with disentangling potential channels and mechanisms through which individuals' locus of control can affect agricultural investment decisions, we can theoretically envisage at least three potential mechanisms. Firstly, psychological studies argue that locus of control is a manifestation and one component of self-control (Rosenbaum, 1980).[6] This implies that a poor level of non-cognitive skills may intensify (imply) self-control problems, which in turn affect savings behavior, and hence perpetuate underinvestment in the agricultural sector. Along this line, recent studies show that locus of control significantly predicts savings behavior (Cobb-Clark et al., 2016; Abay et al., 2016b). Secondly, recent behavioral studies exploring the psychological implications of poverty argue that poverty may affect quality of decision making, including agricultural investment decisions (Bertrand et al., 2004; Mullainathan and Shafir, 2013; Haushofer and Fehr, 2014; Bernheim et al., 2015). Mullainathan and Shafir (2013) argue that poverty can impede individuals' cognitive functioning and decision making behavior, a process that may pronounce behavioral biases among poor households. Given the interaction between cognitive and non-cognitive skills (Heckman et al, 2006), locus of control may therefore influence investment decisions by shaping individuals' cognitive and non-cognitive ability to process intertemporal decisions. Lastly, recent theoretical and experimental studies which associate underinvestment in the agricultural sector with aspiration failures also provide another plausible channel through which locus of control may influence agricultural investments (Bernard et al., 2014; Dalton et al., 2014). Bernard et al. (2014) find that some behavioral interventions that were supposed to improve farmers' aspirations also improved locus of control, suggesting that locus of

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[6] The items commonly used to elicit individuals' locus of control are included in Rosenbaum's (1980) index of self-control.

control may influence agricultural investment decisions through its implication on aspiration formation.

III. Context and data

The empirical analysis in this paper focuses on technology adoption decisions of rural households in Ethiopia. Ethiopia provides an interesting context to investigate the implication of farmers' behavioral and psychological capital on their technology adoption decisions. While the Government of Ethiopia continues to invest substantial resources to facilitate the adoption and diffusion of agricultural technologies, agricultural intensification measured in terms of chemical fertilizers and improved seeds use remains low (Morris et al., 2007; Rashid et al., 2013). Explaining the low levels of agricultural intensification and exploring the implication of farmers' internal constraints on their adoption decisions requires further research.

We employ two longitudinal datasets that complement each other. The first longitudinal dataset provides large coverage while the second longitudinal data embeds several hypothetical survey-based questions that may provide some important behavioral attributes to explain technology adoption decisions. The first-stage empirical analysis in this study is based on a large longitudinal dataset collected for evaluating Ethiopia's Agricultural Growth Program (AGP). We will refer to this dataset as the AGP dataset. The AGP dataset was collected by the Central Statistical Agency (CSA) of Ethiopia and the International Food Policy Research Institute (IFPRI), and covers around 7,500 farm households visited twice in two rounds (2011 and 2013). The AGP aims at increasing agricultural productivity and market access for Ethiopia's high agricultural potential zones (in 83 targeted *woredas*) in the four main regions of the country, namely Amhara, Oromiya, SNNP, and Tigray.[7] The evaluation of the AGP and hence survey sampling design involved a random sample of AGP (61 *woredas*) and comparable non-AGP (32) *woredas*. The second step of the sampling design involved random sampling of 3 Enumeration Areas (villages) from each *woreda* and 26 households from each EA (village). Berhane et al. (2013a) provide details on the sampling design of the AGP dataset. The AGP dataset has interesting features that are well-suited for pursuing rigorous investigations on the implications of farmers' behavioral and psychological capital

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[7] Woreda stands for an administrative unit in Ethiopia that corresponds to district. The EA is a statistical area that is representative of the Kebelle. Kebelle is the smallest administrative unit in Ethiopia which may correspond to village.

on their technology adoption decisions. It provides large coverage of the most important agricultural potential areas and key agro-ecological zones in the country, which provide substantial variation in input use and adoption decisions. As the dataset was collected for the purpose of evaluating agricultural productivity and technology adoption, we have detailed information on household characteristics and access to and use of agricultural inputs. The dataset also contains self-reported information on farmers' behavioral and psychological capital, including locus of control.

The second longitudinal dataset we employ in this study comes from a randomized control trial conducted for evaluating the demand for weather-index crop insurance in Ethiopia. This dataset was collected by the International Food Policy Research Institute (IFPRI) and the University of Oxford. The randomization (and associated household survey) covers four *woredas* (districts) in the Oromia region of Ethiopia, namely *Adama*, *Shashemene*, *Dodota*, and *Bako-Tibe* (see Berhane et al., 2013b for details). A total of 110 villages were randomly selected, from which around 2,300 rural households were randomly selected. The intervention involved a random (village level) offer of weather-index crop insurance for 60 villages. Although this intervention (insurance offer) may not influence our key explanatory variable, locus of control, we capture this attribute of the dataset by controlling for village-level dummies for the reason that the treatment can affect farmers' technology adoption decisions. This longitudinal dataset includes three rounds, including a baseline (2011), midline (2012) and endline (2013) surveys. These surveys extract rich information on household demographic and socioeconomic characteristics. Interestingly, these household surveys also administer some hypothetical questions to elicit farmers' behavioral decisions and self-reported information on various outcomes of interest including locus of control, time preferences and risk aversion. We will refer to this dataset as the insurance dataset.

In this paper we are interested in investigating the implication of farmers' locus of control on the adoption of various agricultural technologies. We specifically focus on three agricultural technologies: chemical fertilizers, improved seeds and irrigation. We also employ measures capturing farmers' willingness to adopt a hypothetical technological offer. Using these alternative types of agricultural technologies helps to probe the robustness of our results to alternative explanations. Household-heads are expected to make much of the agricultural adoption decisions in rural Ethiopia. Hence, we focus on investigating the implication of household-heads' locus of

control, by excluding cases where the respondent is not the household-head. This was done for both datasets and reduces the original sample sizes in these datasets

In Table 1, we present the adoption rates of the three agricultural inputs as well as descriptive statistics of the variables of interest from the AGP dataset. About 59% of households applied chemical fertilizers. The adoption of other inputs, improved seeds and irrigation practices, were rather low compared to chemical fertilizers adoption rate. Table A1 (in the Appendix) provides summary statistics of the variables from the insurance dataset. Comparing both datasets, much of the descriptive figures associated with many of the observable characteristics are comparable, except that the insurance dataset shows slightly higher adoption rates for some of the agricultural inputs. This is anticipated for the reason that the AGP data covers a large geographical area within the country, while the insurance dataset comes from four districts (*woredas*) with high agricultural potential.

Table 1: Description of the explanatory variables and their definitions (AGP Dataset)

Variable of interest	Variable description	Mean	SD
Technology adoption (outcome variables)			
Chemical fertilizers	Dummy=1 if HH adopt chemical fertilizers	0.590	0.492
Improved seeds	Dummy=1 if HH adopt improved seeds	0.244	0.430
Irrigation	Dummy=1 if HH practices irrigation	0.062	0.242
Household (farmer) characteristics			
Age	Age of the farmer (household head)	43.983	14.828
Gender	Gender of the household head (1=male)	0.703	0.457
Education	Level of education (0= no education, 13= college education)	1.369	2.553
Household size	Number of household members	4.823	2.111
Socioeconomic standing of households			
Oxen	Number of oxen owned by the household	1.110	1.427
Total land size (ha)	Size of total landholding of the household	2.171	2.749
Self-reported wealth: rich	Dummy =1 if a HH perceive as rich	0.030	0.169
Self-reported wealth: medium	Dummy =1 if a HH perceive as middle class	0.603	0.489
Self-reported wealth: poor	Dummy =1 if a HH perceive as poor	0.367	0.482
Information on crop choice			
Household produces *teff*	Dummy =1 if a household produces *teff*	0.400	0.490
Household produces wheat	Dummy =1 if a household produces wheat	0.293	0.455
Household produces maize	Dummy =1 if a household produces maize	0.564	0.496
Household produces barley	Dummy =1 if a household produces barely	0.301	0.459
Access to extension, information and market			
Number of extension visits	Number of visits by extension agents	1.326	5.682
Household owns radio	Dummy =1 if a household owns radio	0.252	0.434

Member of cooperatives	Dummy =1 if a household is a member of cooperatives	0.169	0.375
Distance to the nearest market (km)	Distance to the nearest market (in *km*)	13.469	11.460
Access to road	Dummy =1 if there is access to road	0.555	0.497
Number of observations (*N*T*)		10550	

Notes: This table provides descriptive statistics of the explanatory variables considered in the analysis. The first column presents mean values while the second column provides standard deviations. SD stands for standard deviation.

3.1. Eliciting locus of control and hypothetical demand for technology

Following the standard practice, we employ Rotter's (1966) scale to elicit farmers' internal and external locus of control. In particular, we employ ten contextually appropriate items which are commonly employed to elicit locus of control (Coleman & DeLeire, 2003; Heckman et al., 2006; Caliendo et al., 2015; Krutikova & Lilleør, 2015). These items are also commonly used to elicit individuals' locus of control in many surveys in Sub-Saharan Africa, including Ethiopia. A list of these items is given in Table A2 (in the Appendix). For each question respondents are asked to provide their response on a six-level Likert-scale of agreement/disagreement.

Although these items (questions) can be intuitively classified to indicate external and internal locus of control, we employ factor analysis to classify the contribution of these items to some latent factors which we interpret as internal and external locus of control. This kind of factor analysis is commonly employed in many studies that aim to investigate the implication of locus of control on various outcomes (Coleman & DeLeire, 2003; Heckman et al., 2006; Caliendo et al., 2015; Krutikova & Lilleør, 2015). Following our factor analysis, the first five items load into a latent factor, which we interpret it as internal locus of control, while the last five items load into another factor which we interpret it as external locus of control. Figure 1 plots the factor loadings (correlations) of these ten items into these two factors. These figures clearly show that the first five items are strongly correlated with the first latent factor (referred to as internal locus of control), while the last five questions are strongly correlated with the second latent factor (referred to as external locus of control). Following iterated factor analysis, we construct two different indexes for internal and external locus of control. To facilitate interpretation, we standardize and employ these indexes in our regressions that characterize farmers' technology adoption decisions. Figures 2 and 3 provide the distribution of these indexes. We also generate indicator (dummy) variables based on the median values of these two continuous indexes and employ them in some of our regressions and robustness exercises. As we employ longitudinal datasets, the construction of these indexes is

based on pooled observations. To capture the longitudinal dimension of the datasets and their implications on these indexes, we employ time dummies in all our regressions. In some of our regressions, we also employ the raw values and responses for some of the items used to elicit locus of control (see Table A5 in the Appendix).
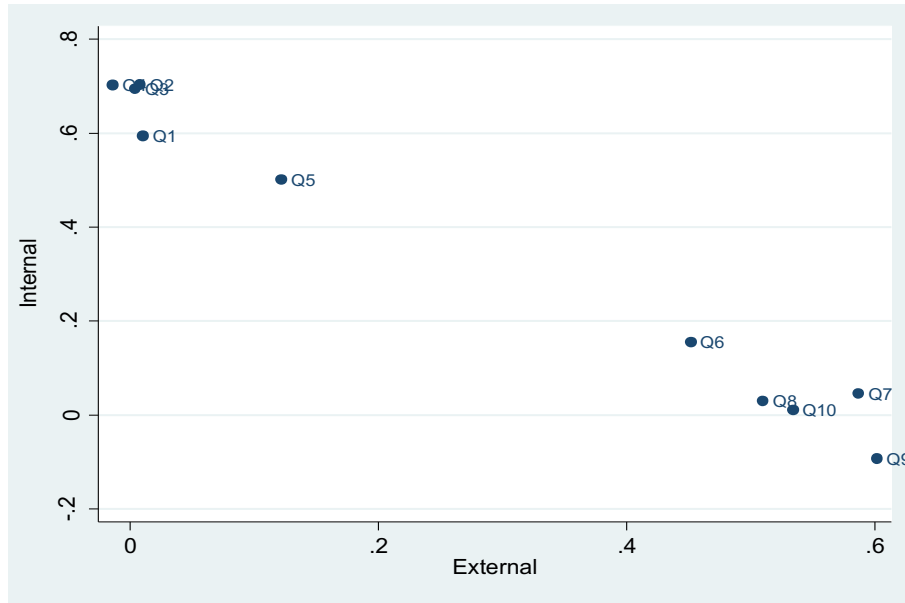
Figure 1: Cross-plot of factor loadings of the items from Rotter (1966) scale.
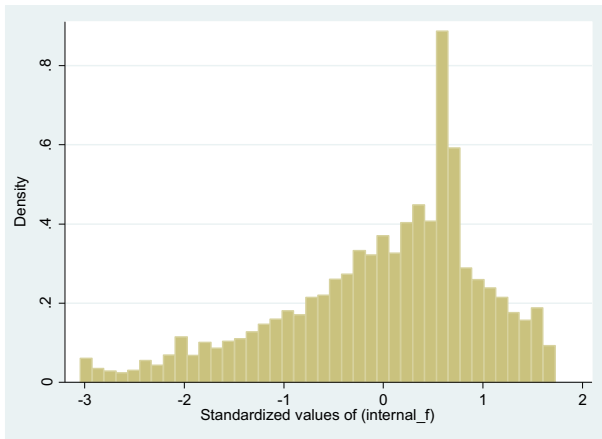
Figure 2: Distribution of internal locus of control (standardized).
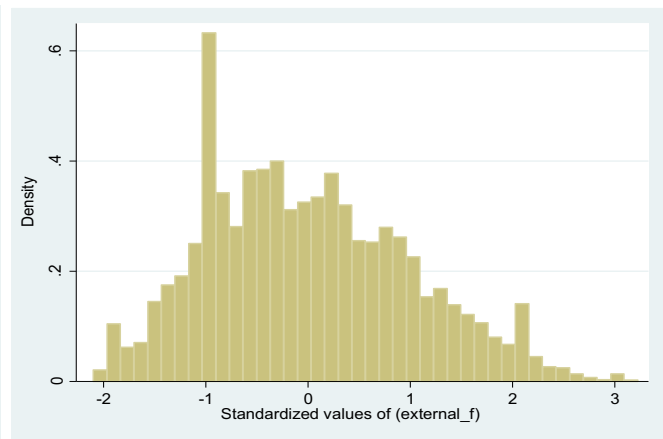
Figure 3: Distribution of external locus of control (standardized).

To characterize these indexes measuring internal and external locus of control, we run some nonparametric and parametric regressions of these indexes on some of the observable characteristics of farmers. Figures 1A and 2A (in the Appendix) provide nonparametric associations between these indexes measuring locus of control and age of farmers. These plots show that internal locus of control decreases (non-linearly) with age while external locus of control increases

with age. These are also observed in similar parametric regressions characterizing farmers' locus of control (see Table A3 in the Appendix). The parametric regressions in Table A3 show that locus of control correlates with some of the observable characteristics of farmers and the patterns of these associations are as anticipated.

Besides the actual agricultural technology adoption decisions, the second dataset (insurance dataset) elicited farmers' willingness to adopt a hypothetically offered new (high-yield) agricultural technology as well as other behavioral attributes related to risk aversion and credit (liquidity) constraints. Farmers were asked about their willingness to adopt a hypothetically offered new agricultural technology using a four level (agreement/disagreement) Likert-scale. These responses included; strongly disagree, disagree, agree, and strongly disagree. From these responses we generate an indicator (dummy) variable showing whether a farmer is willing to adopt a new agricultural technology. Thus, we employ both indicator variables as well as the Likert-scale responses to measure farmers' hypothetical demand for a new agricultural technology. By using this hypothetical demand (stated willingness to adopt a new technology), we explore the implication of locus of control on potential future agricultural investments and related aspirations. Using this stated demand (willingness) to adopt a new agricultural technology may also alleviate potential endogeneity problems that may arise from omitted variables that may affect locus of control as well as actual technology adoption decisions.[8]

To elicit individuals' risk preferences, respondents were given alternative (hypothetical) gambling choices involving progressively increasing risk levels (see Dohmen et al., 2011). Individuals were supposed to choose among hypothetical investment portfolios involving varying levels of risk, starting from not investing up to an investment portfolio involving potential losses (gain). From these choices, we simply generate a five-level ordinal ranking of individuals' risk taking behavior. The insurance dataset also provides information on farmers' level of liquidity (credit) constraints and financial literacy. Farmers were asked whether they have (or are able to borrow) some amount of money for emergency purposes. In particular, the survey asks the following question: *If your household needed X Birr for an emergency, could the household obtain it within*

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[8] The hypothetical nature of the offer also implies that reverse causality problems can be ruled out in these estimations for the reason that these technology adoption decisions do not involve actual investment.

a week?.[9] By changing the amount of *X,* the dataset provides an ordered measure (indicator) of farmers' liquidity (credit) constraint.

IV. Estimation and econometric methods

Empirical identification of the effect of locus of control on technology adoption involves several challenges. Specifically, quantifying the effect of locus of control on farmers' technology adoption may suffer from endogeneity problems arising from omitted behavioral attributes as well as potential reverse causality problems. This is particularly plausible given the potentially intricate relationship between poverty, cognitive (or non-cognitive) functioning and quality of decision-making (Mullainathan & Shafir, 2013; Haushofer & Fehr, 2014; Bernheim et al., 2015). Furthermore, disentangling some of the potential channels through which locus of control can affect agricultural investment decisions is empirically challenging. In view of these empirical challenges, we employ alternative econometric approaches that exploit the cross-sectional as well as longitudinal variations in farmers' psychological capital (locus of control). Considering some assumptions on the nature of our key explanatory variable, locus of control, we estimate the following longitudinal regression:

$$Y_{ft} = {}_f + {}_1(loc_{ft}) + {}_2'X_{ft} + {}_3T_f + {}_3(village_{ft}) + {}_{ft} \tag{1}$$

where Y_{ft} stands for farmers' technology adoption decision (or demand for new agricultural technology) at time *t*. $_f$ stands for farmer-specific random effects or fixed effects. loc_{ft} stands for measures of locus of control (internal and external indexes) as well as indicator variables constructed from these indexes or raw values of the items used to elicit locus of control. T_f represents time dummies that may capture aggregate trends (shifts) in technology adoption or correlated shifts in our explanatory variables. *Village* represents a large set of village-level dummies that may capture geographic and biophysical characteristics that may influence farmers' technology adoption decisions or their demand for agricultural technology. The estimation process involves a stepwise inclusion of important variables. We first run regressions of farmers' technology adoption decisions as a function of their locus of control and other characteristics of households, and later extend the specification by adding village-level fixed effects. In each regression we consider both

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[9] Birr is the Ethiopian currency and 1 USD was equal to17 Birr during the survey year.

linear and non-linear effects of some the continuous variables of interest, by including statistically significant higher order polynomials. Farmers living in the same village are expected to share some unobservable effects, and hence in all regressions we cluster standard errors at village level. For this (clustering) purpose, we will mainly focus on linear regressions approaches, despite the fact that our outcome variables assume binary nature.[10] Besides the standardized indexes measuring locus of control, we also employ binary (indicator) variables based on the median values of these indexes as well as raw values (responses) to some of the items eliciting locus of control.

Technically, we can also estimate equation (1) using fixed effects models by controlling for individual fixed effects. This can be considered as a more conservative and robust empirical strategy, despite the fact that personality traits such as locus of control may not be sufficiently dynamic and truly time-variant. Recent studies show modest short-run and medium-run dynamics in locus of control (Cobb-Clark & Schurer, 2013). Cobb-Clark and Schurer (2013) show that locus control may not be truly time-invariant, and hence using lagged values of locus of control may lead to substantial attenuation bias. Thus, we also estimate equation (1) controlling for individual fixed effects to exploit potential dynamics in locus of control and its implication on farmers' technology adoptions decisions.

V. Results and discussion

In this section, we discuss the key empirical results and their implications. Before embarking on characterizing farmers' technology adoption decisions, some clarifications on interpreting our estimates are important. Without some exogenous variations in farmers' locus of control, the empirical challenges discussed in Section 4 may confound causal inference on the effect of locus of control on agricultural investments. However, even with these problems our empirical analysis provides important insights for two reasons. First, given the alternative econometric approaches and specifications we employ, which exploit both the cross-sectional as well as longitudinal variations in locus of control, we believe that our estimates can at least inform the direction of causality in the relationships between locus of control and agricultural investments (technology

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[10] For some of the regressions we also estimate probit models, and marginal effects from these estimations are included in the Appendix.

adoption).[11] Second, even the associational evidence between locus of control and farmers' technology adoption decisions offer useful insights to explain the existing empirical puzzle associated with the low adoption rates of profitable agricultural technologies in Africa.

Although our estimations exploit the cross-sectional as well as longitudinal variations in locus of control, we first present and focus on the random effects estimates from equation (1) and present the fixed effects estimates at later stage. We first present the results based on the AGP dataset and corroborate these results using the insurance dataset.

5.1. Evidence from the AGP dataset

Table 2 provides estimates of equation (1) for explaining farmers' technology adoption decisions, including chemical fertilizers, improved seeds and irrigation. The first two columns provide results associated with farmers' adoption of chemical fertilizers; the third and fourth columns characterize farmers' use of improved seeds, while the last two columns provide estimates associated with farmers' adoption of irrigation technologies. The estimation results in Table 2 show some interesting insights associated with the implications of farmers' locus of control on technology adoption decisions. More specifically, columns 1–2 of Table 2 indicate that farmers with an internal locus of control (or a greater degree of it) were more likely to use chemical fertilizers in one or more of their plots. On the other hand, farmers with an external locus of control (or a greater degree of it) were less likely to use chemical fertilizers. These results remain robust even when we control for a large set of household characteristics and 240 village-level dummies (fixed effects).[12] These estimates show that one standard deviation increase in the internal locus of control is associated with a 1.5–2 percentage points increase in the probability of using chemical fertilizers. On the other hand, one standard deviation increase in external locus of control is associated with a 1–1.4 percentage points reduction in the probability of using chemical fertilizers. These estimates are reasonably sizeable even compared to the effects of other demographic and socioeconomic attributes of farmers in Table 2. Given that we explain around half of the variations in farmers'

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[11] To confirm this, some of our robustness exercises employ lagged values of locus of control instead of contemporaneous values.

[12] Our surveys provide information on the types of chemical fertilizers. In Ethiopia, Urea and Diammonium Phosphate (DAP) are the two main types of fertilizers commonly applied by farmers. Splitting the fertilizer application into these two types of chemical fertilizers confirms that the implication of farmers' locus of control works for both types of chemical fertilizers.

fertilizer adoption decisions, these estimates are also considerable in terms of explaining the substantial heterogeneities in technology adoption decisions in the dataset.

The results in columns 3-4 of Table 2 provide similar evidence on the implication of locus of control on farmers' adoption of improved seeds. Those farmers with an internal locus of control had a higher propensity to use improved seeds in one or more of their plots. These estimates show that one standard deviation increase in the internal locus of control is associated with a 1.1–1.6 percentage points increase in the probability of using improved seeds in one or more plots. The size of this estimate is reasonably meaningful and even larger than a one-time visit by extension agents, a key policy instrument that is commonly argued to facilitate technology diffusion in Sub-Saharan Africa (Davis et al., 2010; Benin et al., 2011; Krishnan & Patnam, 2014).

The last two columns of Table 2 provide estimates characterizing farmers' propensity to use irrigation technologies. These results consistently show that locus of control significantly predicts use of irrigation technologies. Those farmers with an internal locus of control (or more of it) have a higher propensity for using irrigation technologies. This result remains robust even after controlling for a large set of geographic (village level) information as well as village level clustering of standard errors. This is particularly important for the reason that topographic variations are expected to significantly explain the distribution and access to irrigation technologies. Given the limited access and practice of irrigation technologies in our dataset (6.2%), the size of the estimate is also relatively larger than most of the explanatory variables included in the regression in Table 2.[13] This is particularly important given that many of the explanatory variables employed to explain the adoption of irrigation technologies appear to be statistically insignificant, potentially for the reason that irrigation technologies are mostly supply driven and hence households' demand for irrigation technologies remain inelastic to farmers' characteristics.

Table 2: Locus of control and Technology Adoption: Evidence from AGP data

Explanatory variables	Chemical fertilizer	Chemical fertilizer	Improved Seed	Improved Seed	Irrigation	Irrigation
Locus of control (internal, index)	0.020***	0.015***	0.016***	0.011**	0.008**	0.007**
	(0.006)	(0.005)	(0.006)	(0.005)	(0.004)	(0.003)
Locus of control (external, index)	-0.013**	-0.010**	-0.002	-0.006	0.002	0.005
	(0.006)	(0.004)	(0.006)	(0.005)	(0.004)	(0.003)

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[13] We are also able to observe this by decomposing the explained variation in the regressions to those explanatory variables included in the regression. Simple inspection of the R-squared values for the regressions with and without village-level fixed effects shows that much of the variation in irrigation practices is explained by the village-level effects.

Age of farmer (household head)	-0.001	-0.001***	-0.001**	-0.001**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender of farmer (male)	-0.002	0.015	0.004	0.006	0.007	0.009*
	(0.013)	(0.011)	(0.011)	(0.010)	(0.006)	(0.005)
Education of farmer	0.007***	0.003	0.001	0.002	0.001	0.002
	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)
Household size	0.014***	0.013***	0.006*	0.007***	0.001	0.003**
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)
Number of oxen	0.017***	0.021***	0.012**	0.015***	0.006*	0.005
	(0.005)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)
Total land size (ha)	0.001	0.005**	0.001	0.006**	0.001	0.004
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Self-reported wealth: rich	0.028	0.031	0.087***	0.078***	0.007	0.013
	(0.026)	(0.022)	(0.026)	(0.023)	(0.017)	(0.015)
Household produces *Teff*	0.188***	0.160***	0.085***	0.061***	0.020*	-0.006
	(0.021)	(0.017)	(0.019)	(0.014)	(0.011)	(0.008)
Household produces wheat	0.285***	0.199***	0.075***	0.085***	0.018	0.004
	(0.022)	(0.023)	(0.023)	(0.026)	(0.014)	(0.011)
Household produces maize	0.119***	0.107***	0.221***	0.142***	0.016	0.017
	(0.021)	(0.019)	(0.022)	(0.025)	(0.011)	(0.011)
Household produces barley	0.145***	0.106***	0.030	0.011	0.007	0.002
	(0.025)	(0.023)	(0.021)	(0.022)	(0.011)	(0.011)
Number of extension visits	0.001	0.001	0.003***	0.002***	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Household owns Radio	0.053***	0.044***	0.019	0.025**	0.006	0.006
	(0.014)	(0.011)	(0.013)	(0.011)	(0.010)	(0.008)
Household is a member of cooperatives	0.097***	0.050***	0.125***	0.055***	0.015	0.012
	(0.020)	(0.012)	(0.023)	(0.013)	(0.014)	(0.010)
Distance to the nearest market (in *km*)	-0.002**	0.003**	-0.001	0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Access to road	0.020	-0.062**	0.023	-0.014	0.027*	0.074***
	(0.023)	(0.028)	(0.020)	(0.030)	(0.015)	(0.026)
Time dummy	Yes	Yes	Yes	Yes	Yes	Yes
Village dummies (240)	No	Yes	No	Yes	No	Yes
Constant	0.204***	0.054	0.003	-0.021	0.025	-0.102*
	(0.040)	(0.063)	(0.029)	(0.069)	(0.023)	(0.061)
R-squared	0.244	0.479	0.134	0.354	0.037	0.292
Number of observations (N*T)	10209	10209	10209	10209	10209	10209

Notes: This table provides estimates from linear probability (random effects) models for farmers' adoption of the three agricultural technologies considered. The first two columns are estimates for fertilizer adoption propensities; the third and fourth columns provide estimates for farmers' probability of using improved seeds, while the last two columns provide estimates characterizing farmers' propensity to use irrigation technologies. In this table, locus of control is measured by two (standardized) indexes measuring farmers' internal and external degree of control over life events. In all regressions, standard errors are clustered at village level and given in parentheses. Asterisks: *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

We can also establish the above empirical results using discrete measures of locus of control (by constructing indicator variables for those individuals with internal and external indexes above the medians) and using probit models. Marginal effects from probit regressions considering both continuous and indicator (discrete) measures of locus of control are given in Table A4 (in the Appendix). These marginal effects in Table A4 confirm the linear regression estimates in Table 2. We also employ some of the raw values of the items used to elicit locus of control. Considering the factor loadings (correlations) in Figure 1, we employ two items with the strongest correlations (factor loadings) with the internal locus of control and two items with the strongest correlations with farmers' external locus of control.[14] Table A5 (in the Appendix) shows that the two items associated with internal locus of control were positively and significantly correlated with the adoption of the three agricultural technologies, while those items measuring external locus of control were negatively associated with farmers' adoption propensities. The size and strength of the associations are very comparable across the items measuring internal (external) locus of control, confirming that these items captured similar information. These results suggest that the implication of locus of control on technology adoption remains robust to alternative measures of these non-cognitive skills.

More generally, the key results in Table 2 show that farmers' locus of control significantly predicts a range of technology adoption decisions, including the use of chemical fertilizers, improved seeds and irrigation. Those farmers with an internal locus of control, that is, those who perceive that life outcomes can be sufficiently influenced, were more likely to adopt modern agricultural technologies while the reverse seems to hold for those with an external locus of control. These results imply that locus of control may influence (at least explain) agricultural investments as they do human capital (Coleman & DeLeire, 2003; Heckman et al., 2006), health related (Chiteji, 2010; Cobb-Clark et al., 2014) and physical investments (Cobb-Clark et al., 2016). Intuitively, these results suggest that improving farmers' psychological capital may boost agricultural investments and hence play a crucial role in reducing poverty. That is, poor levels of psychological capital or non-cognitive skills may perpetuate poverty by discouraging agricultural investments. These results emphasize that policies that aim to ensure agricultural transformations in Africa may need to

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[14] The factor loadings in Figure 1 show that the second and third items have the highest loadings (correlations) with farmers' internal locus of control, while the ninth and seventh items have the highest loadings (correlations) with farmers' external locus of control. Thus, we employ these items in our regressions (see Table A5 in the Appendix).

consider interventions that can address farmers' internal constraints and behavioral biases which may affect long-term investment decisions.

The estimation results associated with the remaining explanatory variables are broadly consistent with previous evidence. For instance, the results show that those households headed by literate farmers and those with a larger family size are more likely to adopt one or more of the agricultural technologies considered in this study. Similarly, those households with better socioeconomic standing, measured by livestock (land) ownership and self-reported wealth status, have a higher propensity to adopt one or more of these agricultural technologies. These might be potentially driven by economies of scale, risk aversion and liquidity constraints (Knight et al., 2003; Giné & Klonner, 2005; Zerfu & Larsen, 2010). As expected, crop choices of farmers also significantly predicted farmers' propensity to adopt agricultural technologies, particularly chemical fertilizers and improved seeds adoption (see also, Sheahan & Barrett, 2014). Finally, farmers' access to various agricultural technologies, measured by access to extension services and information, significantly predicted farmers' propensity to adopt agricultural technologies, particularly for those technologies that require access to market and information. These results are consistent with previous empirical results which highlight the role of external constraints in explaining farmers' technology adoption dynamics (see, for example, Moser & Barrett, 2006; Giné & Klonner, 2007; Duflo et al., 2011; Minten et al., 2013). These results highlight the need for policy interventions that may alleviate external constraints of poor farmers in Africa, and hence support some of the existing interventions which are supposed to improve rural farmers' access to markets and insurance for agricultural technologies.

Combining the results associated with the implication of farmers' locus of control and those of external constraints (for example, access to credit) reinforces the need for more integrated policies to improve agricultural investments, and hence address poverty traps of different causes. Ghatak (2015) discusses poverty traps that might be driven both by external and internal constraints of farmers. He argues that to the extent that different types of poverty traps are caused by external and internal frictions, no single intervention may alleviate all types of poverty traps. This is particularly the case for rural households suffering from external frictions (market imperfections) and internal constraints. Implicitly, this requires integrating public policies that address external frictions and those which are designed to alleviate extreme scarcity and associated internal biases of rural farmers. These types of policy interventions are particularly appealing for the reason that these

external constraints can interact with farmers' internal constraints. For instance, shocks are shown to erode farmers' psychological capital (Krutikova & Lilleør, 2015); implying that access to insurance markets may alleviate these adverse effects.

In terms of explaining the overall variation in technology adoption decisions among farmers, we can argue that our empirical specifications reasonably account for a substantial share of the heterogeneities in technology adoption decisions. As documented by previous studies, a large amount of these variations are explained by the large-set of village-level dummies, highlighting the role of geographic and biophysical characteristics in explaining farmers' technology adoption decisions (see, for example, Sheahan & Barrett, 2014). However, the implication of locus of control in explaining some level of heterogeneity in farmers' technology adoption remains robust even to such saturated empirical specifications.

5.2.   Evidence from the insurance dataset

Table 3 provides estimates (random effects) of equation (1) using the insurance dataset. These results broadly show that those farmers with an internal locus of control were more likely to adopt all the agricultural technologies considered. These results remain consistent even after controlling for a large set of household characteristics and about 110 village-level fixed effects. The magnitudes of these estimates are comparable to those estimates from the AGP dataset. We also found consistent evidence using discrete measures of locus of control by constructing indicator variables for those individuals with internal and external indexes above the medians (see Table A6 in the Appendices). Given that the AGP dataset and the insurance dataset come from different parts of Ethiopia, our results suggest that the relationships between locus of control and investment in agricultural technologies are robust.

The remaining estimates associated with the other explanatory variables are broadly consistent with those estimates from the AGP dataset as well as previous evidence in the literature. Those households with better literacy and socioeconomic standing are generally more likely to adopt one or more of the agricultural technologies. Those farmers with some liquidity (credit) constraints were less likely to adopt some of the agricultural technologies, particularly those that require some liquid assets and investments. This is consistent with earlier studies which highlight the role of credit market imperfections in impeding agricultural investments and structural

transformation (Croppenstedt et al., 2003; Moser & Barret, 2006; Giné & Klonner, 2007; Zerfu & Larsen, 2010; Duflo et al., 2011).

Table 3: Locus of control and Technology Adoption: Evidence from the Insurance Dataset

Explanatory variables	Chemical fertilizer	Chemical fertilizer	Improved seed	Improved seed	Irrigation	Irrigation
Locus of control (internal, index)	0.033***	0.017***	0.042***	0.032***	0.014***	0.012**
	(0.006)	(0.006)	(0.007)	(0.008)	(0.004)	(0.005)
Locus of control (external, index)	-0.003	0.006	-0.004	0.004	0.002	0.001
	(0.005)	(0.005)	(0.006)	(0.006)	(0.004)	(0.004)
Risk-preference (risk-taking)		0.001		0.007*		-0.001
		(0.004)		(0.004)		(0.002)
Gender of farmer (male)		0.023		-0.007		0.019*
		(0.022)		(0.019)		(0.011)
Age of farmer (household head)		-0.001***		-0.002***		0.000
		(0.000)		(0.000)		(0.000)
Education of farmer		0.004*		-0.002		0.003*
		(0.002)		(0.002)		(0.002)
Household size		0.006**		0.009***		0.001
		(0.003)		(0.003)		(0.002)
Religion: Muslim		0.022		0.111*		-0.039
		(0.035)		(0.064)		(0.059)
Religion: Orthodox		0.007		0.060		-0.035
		(0.030)		(0.063)		(0.059)
Religion: Protestant		0.010		0.060		-0.027
		(0.030)		(0.064)		(0.059)
Social capital		0.001		0.003*		-0.000
		(0.001)		(0.001)		(0.001)
Religiosity		-0.001**		0.001		0.001
		(0.000)		(0.001)		(0.001)
Financial literacy		0.003		0.008		0.011
		(0.013)		(0.014)		(0.009)
Liquidity (credit) constraint		-0.042***		-0.022**		0.002
		(0.008)		(0.010)		(0.005)
Land size (hectare)		0.009**		0.008		0.017***
		(0.004)		(0.006)		(0.005)
Log (value of livestock)		0.028***		0.014***		0.001
		(0.003)		(0.003)		(0.002)
Covariate shocks in the last 10 years		-0.011		0.025		-0.017
		(0.016)		(0.018)		(0.012)
Idiosyncratic shocks in the last 10 years		-0.018*		0.012		0.001
		(0.011)		(0.013)		(0.009)
Trust in financial institutions		0.011		-0.010		0.002
		(0.007)		(0.009)		(0.006)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Village dummies (110)	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.614***	0.378***	0.570***	0.366***	-0.001	-0.047

R-squared	0.172	0.254	0.278	0.305	0.384	0.390
Number of observations (N*T)	5232	4930	5232	4930	5223	4930

Notes: this table provides estimates from linear probability (random effects) models for the three agricultural technologies considered. The first two columns are estimates for farmers' fertilizer adoption propensities. Columns 3 and 4 provide estimates for farmers' probability of using improved seeds, while the last two columns provide estimates characterizing farmers' irrigation practices. In this table, locus of control is measured by two (standardized) indexes standing for internal and external degree of control over life events. In all regressions, standard errors are clustered at village level and given in parentheses. Asterisks: *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

5.3.   Evidence from hypothetical demand for agricultural technology

Besides farmers' actual technology adoption decisions, we also elicited and examined farmers' willingness to adopt a new technology using a hypothetical offer of new high-yield agricultural technology. By doing so, we were able to mitigate some confounding factors that may influence locus of control and actual technology adoption decisions. For instance, poverty and liquidity constraints may directly correlate with locus of control as well as farmers' actual technology adoption decisions. However, these attributes may not directly influence farmers' hypothetical demand to a freely-available new agricultural technology, despite potential indirect effects through other mediating factors. Table 4 provides estimates for farmers' demand (willingness) to adopt a hypothetically offered new agricultural technology. The first three columns are based on the continuous indexes measuring internal and external locus of control, constructed through factor analysis. The last three columns use indicator (dummy) variables constructed based on median values of these indexes measuring internal and external locus of control.

The results in Table 4 consistently confirm the main results based on actual technology adoption decisions. Those farmers with an internal locus of control had a higher demand for (willingness to adopt) a new agricultural technology, suggesting that locus of control may have long-term implications on agricultural investments and aspirations. These results hold both using indicator (dummy) variables as well as Likert-scaled response of farmers' on their willingness to adopt a new technology.[15] The size of these estimates were slightly larger than those estimates based on actual technology adoption decisions, perhaps because hypothetical demand was greater than actual technology adoption decisions of farmers. To probe the information captured in farmers' hypothetical demand for agricultural technology, we ran simple unconditional and

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[15] Estimates based on Likert-scaled responses are given in Table A7 (in the Appendix).

conditional regressions of actual adoption decisions on this hypothetical demand for agricultural technology. The simple regressions in Table A8 (in the Appendix) show that the hypothetical demand for new agricultural technology significantly predicted all actual technology adoption decisions, including chemical fertilizers, improved seeds and irrigation. This may suggest that farmers' hypothetical demand for agricultural technology may provide some valuable information and predictions about their actual adoption decisions.

The overall results associated with farmers' hypothetical demand for agricultural technology suggest that psychological capital (locus of control) of farmers may explain current and future agricultural investment decisions. This is plausible considering previous evidence on the link between locus of control and aspirations (see, for example, Bernard et al., 2014) as well as the relationship between aspirations and agricultural investments (Ray, 2006; Dalton et al., 2014). Interestingly, many of the observable characteristics of farmers which were expected to influence actual technology adoption decisions also predicted farmers' willingness to adopt a freely-available new agricultural technology. For instance, those farmers with binding liquidity (credit) constraint had lower hypothetical demand for the new technology offered. These results might corroborate previous evidence on the psychological implications of poverty in intertemporal decision-making and aspiration formation (Ray, 2006; Mullainathan & Shafir, 2013; Bernard et al., 2014; Dalton et al., 2014; Haushofer & Fehr, 2014). This again emphasizes the importance of addressing rural households' internal constraints and behavioral biases.

Table 4: Locus of Control and Hypothetical Demand for Technology: Evidence from Insurance Data

Explanatory variables	Demand	Demand	Demand	Demand	Demand	Demand
Locus of control (internal, index/dummy)	0.073***	0.055***	0.049***	0.122***	0.091***	0.077***
	(0.006)	(0.007)	(0.007)	(0.010)	(0.011)	(0.011)
Locus of control (external, index/dummy)	-0.001	-0.001	-0.002	-0.025**	-0.020*	-0.023**
	(0.005)	(0.005)	(0.006)	(0.011)	(0.011)	(0.011)
Risk-preference (risk-taking)		0.007**	0.005		0.007**	0.006
		(0.003)	(0.004)		(0.003)	(0.003)
Gender of farmer (male)		0.029*	0.040**		0.031**	0.042***
		(0.016)	(0.016)		(0.015)	(0.016)
Age of farmer		-0.001*	-0.001		-0.001**	-0.001*
		(0.000)	(0.000)		(0.000)	(0.000)
Education of farmer		0.004*	0.003		0.003	0.003
		(0.002)	(0.002)		(0.002)	(0.002)
Household size		0.004	0.004*		0.004*	0.005**
		(0.003)	(0.003)		(0.003)	(0.003)

Religion: Muslim		0.032	0.079		0.024	0.074
		(0.039)	(0.050)		(0.037)	(0.048)
Religion: Orthodox		0.010	0.049		0.006	0.045
		(0.039)	(0.045)		(0.038)	(0.044)
Religion: Protestant		-0.029	0.040		-0.041	0.036
		(0.039)	(0.045)		(0.037)	(0.044)
Social capital		-0.003***	-0.003***		-0.002***	-0.003***
		(0.001)	(0.001)		(0.001)	(0.001)
Religiosity		-0.001***	-0.001**		-0.001***	-0.001**
		(0.000)	(0.001)		(0.000)	(0.001)
Financial literacy		0.027**	0.025**		0.028**	0.026**
		(0.011)	(0.011)		(0.011)	(0.011)
Liquidity (credit) constraint		-0.018**	-0.019**		-0.018**	-0.018**
		(0.007)	(0.008)		(0.007)	(0.008)
Land (hectare)		0.009***	0.005		0.009***	0.005
		(0.003)	(0.004)		(0.003)	(0.004)
Log (value of livestock)		0.004	0.003		0.005**	0.004*
		(0.003)	(0.003)		(0.003)	(0.003)
Covariate shocks in the last 10 years		-0.001	0.009		-0.003	0.006
		(0.013)	(0.014)		(0.013)	(0.014)
Idiosyncratic shocks in the last 10 years		0.019*	0.028**		0.019*	0.028**
		(0.010)	(0.012)		(0.010)	(0.012)
Trust in financial institutions		0.061***	0.067***		0.067***	0.073***
		(0.008)	(0.009)		(0.008)	(0.009)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Village dummies (110)	No	No	Yes	No	No	Yes
Constant	0.835***	0.596***	0.526***	0.785***	0.544***	0.483***
	(0.010)	(0.062)	(0.070)	(0.013)	(0.063)	(0.070)
R-squared	0.045	0.077	0.129	0.034	0.073	0.126
No. of observations (N*T)	5225	4928	4928	5293	4983	4983

Notes: this table provides estimates from linear probability (random effects) models for farmers' hypothetical demand for agricultural technology. The first three columns are based on continuous indexes measuring internal and external locus of control, while the last three columns are estimates based on indicator (dummy) variables constructed using the median values of these indexes. In all regressions, standard errors are clustered at village level and given in parentheses. Asterisks: *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

5.4. Fixed effects results

Despite the fact that personality traits such as locus of control may not be truly dynamic, particularly in the very short-term, we also estimate our regressions using (farmer) fixed effects models. We do so using both datasets and both for farmers' actual adoptions decisions as well as their hypothetical demand for a new agricultural technology. These regressions aim to explore the implication of potential dynamics in farmers' locus of control on farmers' technology adoption

dynamics. Tables 5 to 7 provide fixed effects estimates for both datasets and for farmers' actual and hypothetical demand for agricultural technologies. Overall, the fixed effects results were consistent with the random effects results established in the previous sections. These results hold for both datasets as well as for continuous indexes and discrete measures of farmers' locus of control. The magnitudes of these associations are also comparable with those based on cross-sectional variations established in section 5.1 to 5.3. For both datasets, one standard deviation increase in internal locus of control is associated with 1.3 to 2.2 percentage points increase in the probability of adopting a specific agricultural technology. The fixed effects results associated with farmers' willingness to adopt a new agricultural technology were also consistent with the random effects estimates. The magnitudes of these estimates in Table 7 are comparable with those estimates given in Table 4. As we employ dummy variables for technology adoption decisions, it is less likely that measurement errors can account for the strong correlations in the dynamics of farmers' locus of control and their technology adoption decisions.

In sum, the fixed effects results suggest that potential dynamics in farmers' locus of control may have substantial implications on farmers' technology adoption decisions. These results can be considered as more conservative estimates compared to those estimates based on the cross-sectional variations in farmers' locus of control. The prevalence of the strong association between locus of control and a range of agricultural technologies using fixed effects and random effects estimations may imply that the relationship is strong. Furthermore, the robustness of these associations across the two different longitudinal datasets, as well as for revealed and stated measures of technology adoption decisions highlights that this relationship could be meaningful. All these pieces of evidence suggest that a weaker causal interpretation of the associations may be commendable. More specifically, we believe that a conservative interpretation of the associations can at least inform the direction of causality in the relationship between individuals' locus of control and the range of agricultural technologies considered.

Table 5: Locus of Control and Technology Adoption: Evidence from the AGP Dataset

Explanatory variables	Chemical fertilizer	Improved seed	Irrigation
Locus of control (internal, index)	0.019***	0.013*	0.021***
	(0.006)	(0.006)	(0.005)
Locus of control (external, index)	-0.005	-0.005	0.012**
	(0.006)	(0.006)	(0.006)

Time dummy			Yes	Yes	Yes	
Household (farmer) fixed effects			Yes	Yes	Yes	
Constant			0.590***	0.244***	0.062***	
			(0.000)	(0.000)	(0.000)	
No. of observations (N*T)			10543	10543	10360	

Notes: this table provides estimates from fixed effects linear regressions for the three agricultural technologies considered in this study. The first column provides estimates for farmers' use of chemical fertilizers; the second column provides estimates for farmers' propensity to use improved seeds, while the third column provides estimates for farmers' likelihood of using irrigation technologies. In all regressions, standard errors are clustered at village level and given in parentheses. Asterisks: *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Table 6: Locus of Control and Technology Adoption: Evidence from the Insurance Dataset

Explanatory variables	Chemical fertilizer	Chemical Fertilizer	Improved seed	Improved Seed	Irrigation	Irrigation
Locus of control (internal, index)	0.017**	0.017**	0.023***	0.022**	0.011**	0.011**
	(0.007)	(0.007)	(0.009)	(0.008)	(0.005)	(0.005)
Locus of control (external, index)	0.005	0.005	-0.012	-0.012	-0.001	-0.003
	(0.006)	(0.006)	(0.007)	(0.007)	(0.004)	(0.003)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Other covariates	No	Yes	No	Yes	No	Yes
Household (farmer) fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.826***	0.880***	0.858***	0.865***	0.062***	0.033*
	(0.007)	(0.018)	(0.015)	(0.032)	(0.005)	(0.018)
No. of observations (N*T)	5232	5107	5232	5107	5223	5107

Notes: this table provides estimates from fixed effects (linear probability model) regressions for the three agricultural technologies considered in this study. The first two columns provide estimates for farmers' use of chemical fertilizers. The third and fourth columns provide estimates for farmers' propensity to use improved seeds. The last two columns provide fixed effects results for farmers' propensity to use irrigation technologies. In all regressions, standard errors are clustered at village level and given in parentheses. Asterisks: *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Table 7: Locus of Control and Hypothetical Demand for Technology: Evidence from the Insurance Dataset

Explanatory variables	Demand	Demand	Demand	Demand
Locus of control (internal, index/dummy)	0.056***	0.044***	0.088***	0.067***
	(0.008)	(0.008)	(0.013)	(0.013)
Locus of control (external, index/dummy)	0.004	0.002	-0.021	-0.022
	(0.008)	(0.007)	(0.014)	(0.014)
Constant	0.832***	0.637***	0.797***	0.606***
	(0.009)	(0.043)	(0.012)	(0.042)
Time dummies	Yes	Yes	Yes	Yes
Other covariates	No	Yes	No	Yes
Household (farmer) fixed effects	Yes	Yes	Yes	Yes
R-squared	0.134	0.194	0.111	0.176
No. of observations (N*T)	5225	4928	5225	4928

Notes: this table provides estimates from fixed effects (linear probability model) regressions for farmers' hypothetical demand for a new agricultural technology. The first two columns are based on continuous indexes measuring internal and external locus of control, while the last two columns are estimates based on indicator variables constructed using the median values of these indexes. In all regressions, standard errors are clustered at village level and given in parentheses. Asterisks: *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Although our reduced form equations do not uncover potential mechanisms driving the above associations, we believe that some of the channels we discussed in Section 2 may explain the strong relationships between locus of control and agricultural investments. The intrinsic relationship between locus of control and self-control (Rosenbaum, 1980), and the implication of the latter on investment and intertemporal choices insinuates that self-control may drive some of these associations. Using the same dataset, Abay et al. (2016b) showed that individuals with an internal locus of control are more likely to save, which may imply that they are also more likely to invest in agricultural technologies. The positive associations between internal locus of control and agricultural investments may also reflect the implication of cognitive and non-cognitive skills in intertemporal planning and decision making (see Mullainathan & Shafir, 2013; Haushofer & Fehr, 2014). The strong associations between locus of control and technology adoption decisions may also imply the role of psychological capital in aspiration formation and hence agricultural investments (see, for example Bernard et al., 2014; Dalton et al., 2014).

VI. Concluding remarks

We provide empirical evidence on the implication of farmers' psychological capital, locus of control, on agricultural technology adoption decisions. In particular, we explored psychological (behavioral) explanations for the slow adoption of profitable agricultural technologies in Sub-Saharan Africa (Ethiopia). We were also able to explain some of the existing unexplained heterogeneities in technology adoption decisions in Sub-Saharan Africa (Suri, 2011; Sheahan & Barrett, 2014; Abay et al., 2016a). We employed two longitudinal datasets that provided detailed information on farmers' actual technology adoption decisions as well as their hypothetical demand for new agricultural technology.

We found that farmers' locus of control significantly predicted the adoption of a considerable list of agricultural technologies, including chemical fertilizers, improved seeds, and

irrigation. Specifically, we show that those farmers with an internal locus of control (or a greater degree of it) were more likely to adopt the above agricultural technologies, while those farmers with an external locus of control seemed less likely to adopt one or more of these agricultural technologies. Our findings show that these results were consistent across both datasets employed as well as across different measures of farmers' locus of control. In addition, we document that these empirical results hold both for farmers' actual technology adoptions as well as farmers' hypothetical demand for agricultural technology. We probed the robustness of our results using alternative estimation strategies that exploit the cross-sectional and longitudinal variations in farmers' non-cognitive skills (locus of control), and we show that the results hold even in a more conservative fixed effects estimation approach, assuming locus of control as a time-variant and dynamic behavioral trait (Cobb-Clark & Schurer, 2013; Cobb-Clark et al., 2014). These results imply that locus of control may influence agricultural investments as it does human capital investments (Coleman & DeLeire, 2003; Heckman et al., 2006) and health related investments (Chiteji, 2010; Cobb-Clark et al., 2014).

We also find that farmers' external constraints, including liquidity constraints, access to information and extension services, explained farmers' technology adoption decisions. Farmers with some liquidity (credit) constraint were less likely to adopt most of the agricultural technologies considered. This result holds both for farmers' revealed and stated (hypothetical) technology adoption decisions, and is consistent with previous evidence on the psychological implications of poverty in intertemporal decision-makings and aspiration formations (Mullainathan & Shafir, 2013; Haushofer & Fehr, 2014; Dalton et al., 2014). Similarly, farmers' access to agricultural technologies, measured by access to extension services and information, was associated to a higher propensity to adopt agricultural technologies. These results are consistent with previous empirical results that highlight the potential of external constraints (including information market imperfections) to explain farmers' technology adoption dynamics in Africa (see, for example, Croppenstedt et al., 2003; Moser & Barret, 2006; Giné & Klonner, 2007; Zerfu & Larsen, 2010; Duflo et al., 2011).

Our results imply that policy instruments that improve rural households' non-cognitive skills may boost agricultural investments. The results suggest that agricultural transformation and anti-poverty policies in Africa may need to address not only external constraints of poor households, but also internal constraints of rural farmers. Interestingly, evolving evidence may guide policy interventions aiming to improve rural farmers' psychological capital and non-cognitive skills. For

instance, Bernard et al. (2014) document some simple behavioral interventions that can improve farmers' locus of control and forward-looking behavior. Abay et al. (2016b) show that locus of control significantly predicts demand for commitment, while Duflo et al. (2011) argue that provision of commitment devices may improve agricultural investments and welfare of rural farmers. These pieces of evidence insinuate that commitment instruments may alleviate some of the internal constraints of rural farmers in Africa.

Given that rural farmers in Ethiopia suffer from external frictions (market imperfections) as well as internal behavioral biases, integrating agricultural policies that address external frictions and internal constraints of poor households may boost agricultural investments, and hence reduce poverty traps. Ghatak (2015) argues that combining policy interventions that address external constraints (for example, relaxing credit constraints) and internal constraints (for example, training on specific skills) of poor households may produce higher returns than would otherwise provide independently. This is particularly appealing in contexts where external and internal constraints coexist. For instance, combining behavioral instruments (for example, training) that improve farmers' level of psychological capital (or aspirations) with (un)conditional cash transfers that address farmers' extent of scarcity may improve farmers' agricultural investments. Along this line, Haushofer and Shapiro (2016) show that unconditional cash transfers in rural Kenya improved farmers' psychological well-being.

However, this study does have some limitations. Despite the strong associations between locus of control and technology adoption decisions, our reduced form approach and associated results do not reveal much about the mechanisms in these associations. Similarly, although some of the associations may plausibly carry causal interpretations, causal inferences concerning these correlations are more complex without some exogenous variations in farmers' locus of control. We hope that further studies will explore the nature and potential mechanisms in these associations as well as the implications of these associations in explaining the agricultural productivity of farmers.

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Appendix

**Table A1: Summary Statistics of Sampled Farmers from the Insurance Data**

Explanatory variables	Mean	Standard deviation
Technology adoption (outcome variables)		
Chemical fertilizers	0.838	0.369
Improved seeds	0.704	0.456
Irrigation technology	0.076	0.265
Hypothetical demand for technology	0.848	0.359
Demographic characteristics		
Gender (1=male)	0.839	0.367
Age (years)	42.548	14.388
Highest educational grade (years)	2.675	31644
Household size	5.876	2.323
Religion: Muslim	0.467	0.499
Religion: Orthodox	0.267	0.443
Religion: Protestant	0.248	0.432
Religion: Other	0.018	0.132
Social capital (number of people to rely on in time of need)	4.608	6.639
Religiosity (number of times attending religious events last month)	7.283	12.724
Financially literate (1=literate)	0.303	0.460
Liquidity constraint level (three-level scale)	1.876	0.835
Socioeconomic characteristics		
Land owned in hectares	1.471	1.379
Value of livestock owned (Birr)	12576.430	15456.560
Exposure to shocks		
Covariate shocks in the last 10 years (1=yes)	0.839	0.367
Idiosyncratic shocks in the last 10 years (1=yes)	0.450	0.498
Risk preferences and trust levels		
Risk-taking behavior (five-level scale)	3.249	1.536
Trust in financial institutions (five-level scale)	2.941	0.723
Number of observations	5293	

Notes: This table provides descriptive statistics of the explanatory variables considered in the analysis. The first column presents mean values while the second column reports standard deviations.

Table A2. Components of (or items eliciting) Locus of control (AGP Data)

Items	Mean	Standard deviation
Internal		
Q1. My life is determined by my own actions.	4.272	1.487
Q2. When I get what I want, it is usually because I worked hard for it.	4.441	1.428
Q3. I am usually able to protect my personal interests.	4.178	1.481
Q4. I can mostly determine what will happen in my life.	4.253	1.513
Q5. When I make plans, I am almost certain/guaranteed/sure to make them work.	4.113	1.512
External		
Q6. To a great extent, my life is controlled by accidental/chance happenings.	3.183	1.667
Q7. I feel like what happens in my life is determined by others.	2.824	1.487
Q8. It is not always wise for me to plan too far ahead because many things turn out to be a matter of good or bad fortune.	3.046	1.531
Q9. My life is chiefly controlled by other powerful people.	2.711	1.496
Q10. People like myself have little chance of protecting personal interest.	3.058	1.441

Notes: This table provides summary statistics of the components of locus of control, given in average response based on six-scale response. The first column presents mean values while the second column provides standard deviations of these responses.
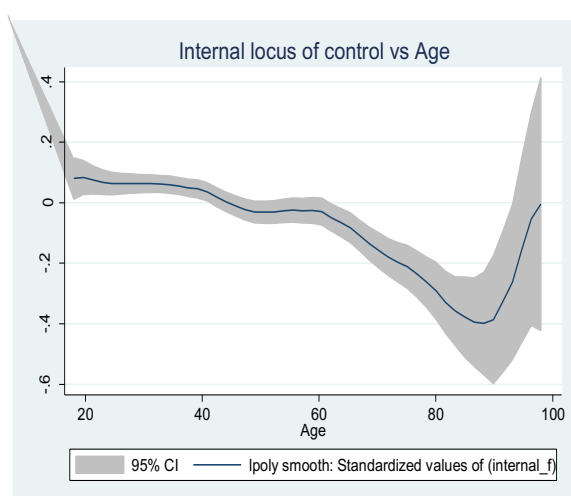
Figure 1A: Nonparametric regression of internality on age.
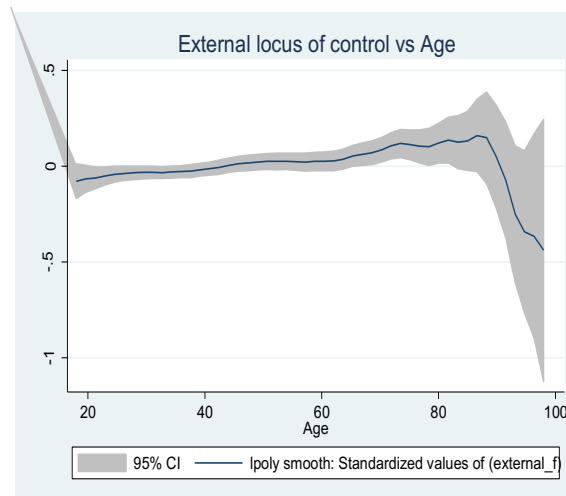
Figure 2A: Nonparametric regression of externality on age

Table A3: Explaining Farmers' Locus of Control: Evidence from AGP data

Explanatory variables	Internal locus of control	External locus of control
Age of farmer (centered at zero)	-0.002***	0.002**
	(0.001)	(0.001)
Age squared (centered at zero)/100	-0.009**	-0.001
	(0.004)	(0.005)
Gender of farmer (male)	0.160***	-0.066***
	(0.023)	(0.023)
Education of farmer	0.004	-0.022***
	(0.005)	(0.004)
Household size	0.009	0.001
	(0.006)	(0.006)
Oxen	-0.002	-0.001
	(0.009)	(0.008)
Total land size (ha)	0.003	-0.006
	(0.005)	(0.005)
Self-reported wealth: rich or medium	0.139***	-0.135***
	(0.026)	(0.026)
Household produces *Teff*	0.001	0.039
	(0.029)	(0.030)
Household produces wheat	-0.013	-0.014
	(0.038)	(0.028)
Household produces maize	-0.003	0.005
	(0.033)	(0.032)
Household produces barley	0.014	-0.051
	(0.037)	(0.035)
Number of extension visits	0.000	-0.001
	(0.003)	(0.002)
Household owns Radio	0.062**	-0.030
	(0.026)	(0.028)
Household is a member of Cooperative	0.011	0.065**
	(0.031)	(0.033)
Distance to the nearest market	0.004	-0.001
	(0.003)	(0.003)
Access to road	-0.054	-0.015
	(0.065)	(0.063)
Constant	-0.519***	-0.600**
	(0.152)	(0.152)
Time dummy	Yes	Yes
Village dummies (240)	Yes	Yes
R-squared	0.162	0.133
Number of observations (N*T)	10209	10209

Notes: this table provides estimates from linear regressions for characterizing the indexes measuring internal and external locus of control. The first column characterizes farmers' internal locus of control while the second

column characterizes farmers' external locus of control. Asterisks: *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Table A4: Marginal Effects from Probit Regressions: Evidence from the AGP Dataset

Explanatory variables	Chemical fertilizer	Improved seed	Irrigation	Chemical fertilizer	Improved seed	Irrigation
Locus of control (internal, index/dummy)	0.025***	0.017***	0.004***	0.043***	0.030***	0.006***
	(0.005)	(0.004)	(0.001)	(0.010)	(0.009)	(0.002)
Locus of control (external, index/dummy)	-0.018***	-0.004	0.001	-0.022**	-0.013	0.003
	(0.005)	(0.004)	(0.001)	(0.010)	(0.009)	(0.002)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Other covariates	Yes	Yes	Yes	Yes	Yes	Yes
Village dummies	No	No	No	No	No	No
Number of observations (N*T)	10209	10209	10209	10209	10209	10209

Notes: This table provides marginal effects from probit models for farmers' adoption of the three agricultural technologies considered. The first three columns are based on two continuous indexes measuring farmers' internal and external locus of control, while the last three columns provide marginal effects using indicator (dummy) variables based on median values of the former indexes. In all regressions, standard errors are clustered at village level and given in parenthesis. Asterisks: *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Table A5: Locus of control and Technology Adoption: Evidence from the AGP Dataset

Explanatory variables	Chemical fertilizer	Improved seed	Irrigation	Chemical fertilizer	Improved seed	Irrigation
Locus of control (item #Q2/Q3)	0.008***	0.007**	0.004**	0.008***	0.006**	0.004*
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Locus of control (item #Q9/Q7)	-0.006**	-0.004*	0.001	-0.006**	-0.004*	0.002
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Time dummy	Yes	Yes	Yes	Yes	Yes	Yes
Other covariates	Yes	Yes	Yes	Yes	Yes	Yes
Village dummies (240)	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.028	-0.043	-0.124**	0.035	-0.036	-0.122**
	(0.065)	(0.069)	(0.061)	(0.065)	(0.072)	(0.061)
R-squared	0.479	0.354	0.292	0.479	0.354	0.292
Number of observations (N*T)	10210	10210	10210	10210	10210	10210

Notes: This table provides estimates from linear probability (random effects) models for farmers' adoption of the three agricultural technologies considered. In this table, we employ the raw values of the items used to elicit (measure) locus of control. We particularly employ two items which are strongly correlated with farmers' internality (items #Q2 and Q3) and two items with strong correlation to farmers' externality (items #Q9 and Q7) (see Figure 1). The first three columns employ one component (item #Q2) for capturing internality and one component (item #Q9) for capturing externality, while the last three columns report similar exercises using the remaining items for capturing farmers' internal and external locus of control. In all regressions, standard errors are clustered at village level and given in parentheses. Asterisks: *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Table A6: Locus of control and Technology Adoption: Evidence from the Insurance Dataset

Explanatory variables	Chemical fertilizer	Chemical fertilizer	Improved seed	Improved Seed	Irrigation	Irrigation
Locus of control (internal, dummy)	0.041***	0.023**	0.063***	0.050***	0.026***	0.025***
	(0.010)	(0.010)	(0.012)	(0.014)	(0.007)	(0.007)
Locus of control (external, dummy)	-0.002	0.016	0.003	0.017	-0.001	-0.002
	(0.010)	(0.010)	(0.011)	(0.011)	(0.006)	(0.006)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Other covariates	No	Yes	No	Yes	No	Yes
Village dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.597***	0.362***	0.537***	0.318***	-0.011	-0.063
	(0.011)	(0.058)	(0.020)	(0.093)	(0.008)	(0.084)
R-squared	0.163	0.253	0.274	0.302	0.377	0.384
Number of observations (N*T)	5309	4986	5309	4986	5299	4986

Notes: this table provides estimates from linear probability models for the three agricultural technologies considered. The first two columns are estimates for fertilizer adoption propensities. In this table, locus of control is measured by two indicator (dummy) variables for internality and externality, constructed using median values of the indexes measuring internal and external locus of control. In all regressions, standard errors are clustered at village level and given in parenthesis. Asterisks: *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Table A7: Locus of Control and Hypothetical Demand (Likert-scale) for Technology: Evidence from the Insurance Dataset

Explanatory variables	Demand	Demand	Demand	Demand	Demand	Demand
Locus of control (internal, index/dummy)	0.258***	0.216***	0.208***	0.456***	0.374***	0.348***
	(0.013)	(0.015)	(0.016)	(0.023)	(0.024)	(0.025)
Locus of control (external, index/dummy)	0.007	0.005	-0.000	-0.017	-0.007	-0.018
	(0.011)	(0.011)	(0.012)	(0.020)	(0.019)	(0.020)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Village dummies (110)	No	Yes	No	Yes	No	Yes
Constant	3.141***	2.500***	2.381***	2.915***	2.279***	2.166***
	(0.018)	(0.114)	(0.125)	(0.022)	(0.113)	(0.122)
R-squared	0.139	0.189	0.237	0.113	0.176	0.223
No. of observations (N*T)	5225	4928	4928	5293	4983	4983

Notes: this table provides estimates from linear regression (random effects) models for farmers' hypothetical demand for a new agricultural technology. In this table, hypothetical demand for new technology is measured by four-level ranking of farmers' willingness to adopt a hypothetically offered new technology. The first three columns are based on continuous indexes measuring internal and external locus of control, while the last three columns are estimates based on indicator variables constructed using median values of these indexes. In all regressions, standard errors are clustered at village level and given in parentheses. Asterisks: *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.

Table A8: Hypothetical Demand and Actual Technology Adoption:
Evidence from the Insurance Dataset

Explanatory variables	Chemical fertilizer	Chemical fertilizer	Improved Seed	Improved seed	Irrigation	Irrigation
Hypothetical demand (Likert-scale)	0.039***	0.042***	0.027***	0.048***	0.018***	0.042***
	(0.007)	(0.007)	(0.009)	(0.009)	(0.006)	(0.007)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Village dummies (110)	No	Yes	No	Yes	No	Yes
Constant	0.696***	0.483***	0.765***	0.422***	0.006	0.483***
	(0.028)	(0.024)	(0.031)	(0.034)	(0.017)	(0.024)
Number of observations (N*T)	5293	5287	5293	5287	5293	5287

Notes: this table provides unconditional and conditional correlations between farmers' actual adoption decisions and their hypothetical demand for agricultural technology. In this table, hypothetical demand for new technology is captured by four-level ranking of farmers' willingness to adopt hypothetically offered new technology. In all regressions, standard errors are clustered at village level and given in parentheses. Asterisks: *, ** and *** indicate statistical significance at 10%, 5% and 1%, respectively.